

1. Example 1

Basic

"We defined two models to describe our data: \mathcal{H}_1 states that mean grade for students who attend Anastasia's tutorials will not be equal to the mean grade for students who attend Bernadette's tutorials. On the other hand, \mathcal{H}_0 states that mean grades will be the same for both tutors. We then computed a Bayesian independent samples t -test (Rouder et al., 2009) to quantify the evidence for \mathcal{H}_1 over \mathcal{H}_0 . We found a Bayes factor of $B_{10} = 1.76$, indicating that the observed data are approximately 1.76 times more likely under \mathcal{H}_1 than \mathcal{H}_0 . According to the recommendations of Jeffreys (1961), this constitutes *anecdotal* evidence for \mathcal{H}_1 over \mathcal{H}_0 ."

Advanced

"We defined two models to describe our data: $\mathcal{H}_1 : \delta \neq 0$ states that mean grade for students who attend Anastasia's tutorials will not be equal to the mean grade for students who attend Bernadette's tutorials. On the other hand, $\mathcal{H}_0 : \delta = 0$ states that mean grades will be the same for both tutors. We then computed a Bayesian independent samples t -test (Rouder et al., 2009) to quantify the evidence for \mathcal{H}_1 over \mathcal{H}_0 . This test requires the user to specify a prior distribution for effect size δ , which we initially took at the default Cauchy prior with scale $r = 0.707$. Using this prior, we found a Bayes factor of $B_{10} = 1.76$, indicating that the observed data are approximately 1.76 times more likely under \mathcal{H}_1 than \mathcal{H}_0 . According to the recommendations of Jeffreys (1961), this constitutes *anecdotal* evidence for \mathcal{H}_1 over \mathcal{H}_0 . Additionally, we performed a robustness check by varying the prior scale factor r , each reflecting a different *a priori* expectation of the effect of our manipulation. Generally, B_{10} decreases as the scale factor r increases, but even using a very wide prior with $r = 1.41$, the inference remains the same, as the data are only 1.32 times more likely under \mathcal{H}_1 than under \mathcal{H}_0 ."

2. Example 2

Basic

"We defined two models to describe our data: \mathcal{H}_1 states that the mean score on the second exam will be greater than the mean score on the first exam, whereas \mathcal{H}_0 states that the mean score will be equal on both exams. We then computed a Bayesian paired-samples t -test (Rouder et al., 2009) to quantify the evidence for \mathcal{H}_1 over \mathcal{H}_0 . We found a Bayes factor of $B_{10} = 11983$, indicating that the observed data are approximately 12,000 times more likely under \mathcal{H}_1 than \mathcal{H}_0 ."

Advanced

"We defined two models to describe our data: $\mathcal{H}_1 : \delta > 0$ states that the mean score on the second exam will be greater than the mean score on the first exam, whereas $\mathcal{H}_0 : \delta = 0$ states that the mean score will be equal on both exams. We then computed a Bayesian paired-samples t -test (Rouder et al., 2009) to quantify the evidence for \mathcal{H}_1 over \mathcal{H}_0 . This test requires the user to specify a

prior distribution for effect size δ , which we initially took at the default Cauchy prior with scale $r = 0.707$. Using this prior, we found a Bayes factor of $B_{10} = 11983$, indicating that the observed data are approximately 12,000 times more likely under \mathcal{H}_1 than \mathcal{H}_0 . Additionally, we performed a robustness check by varying the prior scale factor r , each reflecting a different *a priori* expectation of the effect of our manipulation. B_{10} remained large over a reasonable range of values of r , increasing to $B_{10}=13964$ for $r = 1$ and $B_{10} = 14331$ for $r = 1.41$. In all, these results indicate that our data is strongly evidential of \mathcal{H}_1 over \mathcal{H}_0 ."

References:

1. Jeffreys, H. (1961). *Theory of Probability* (3rd ed.). Oxford University Press.
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3. Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, 56, 356-374.